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Fingerprint Research

Center for Unified Biometrics and Sensors,
University at Buffalo

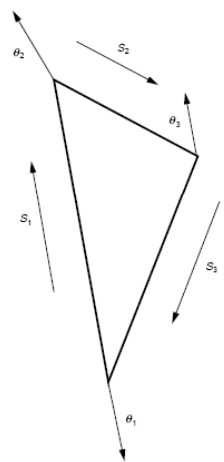


Overview of Research Topics

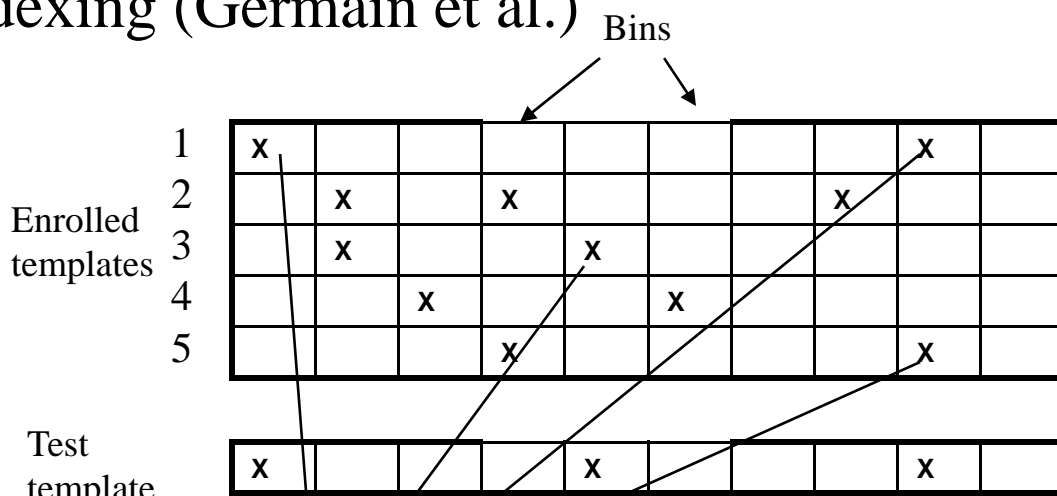
- Image Preprocessing, Segmentation, Binarization
 - STFT based
 - Directional Median Filtering with Adaptive (quality based) Window Size & Harris corner point based segmentation
- Feature (minutia extraction)
 - Contour based; searching for turns in contours
- Minutia Matching
 - Triplet and secondary feature matching
- Verifying Minutia Matching by Correlation Methods
- Fingerprint Indexing
 - Tree based; branches correspond to local minutia geometry
- Cancelable Fingerprint Templates
 - Hashes are symmetric functions of local neighborhood minutiae

Previous Research in Indexing

- Classification into predefined classes (arch, loop, whorl)
- Continuous Classification or Filtering (e.g. Fingerprintcode)
- Triplet based indexing (Germain et al.)



Each minutia triplet is associated with some bin



Retrieved indexes: 1, 3, 1, 5

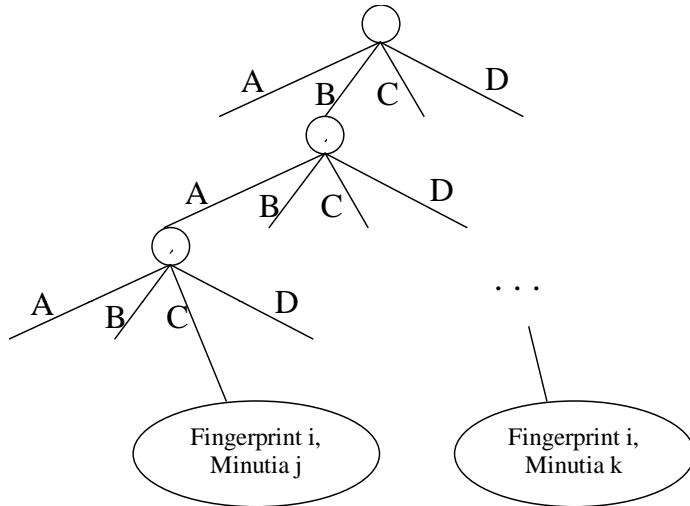
Count fingerprints with most matches: 1(2 times), 3 (1 time), 5 (1 time)



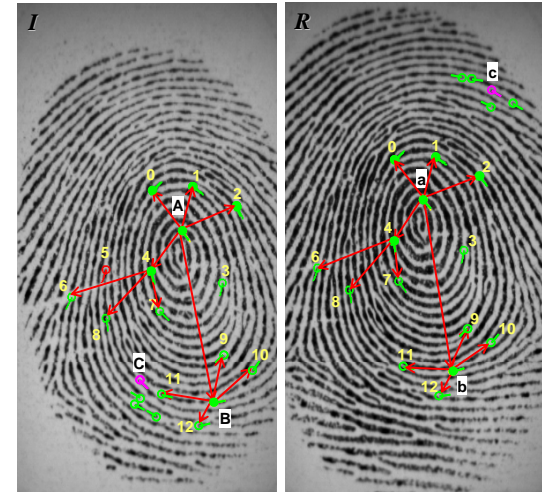
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Indexing Idea

Index structure for fingerprints:



A,B,C,D denote quantization bins of k-plets. Going down the tree is equivalent to the expansion of neighboring k-plet. Note that each fingerprint could be associated with multiple leaf nodes.

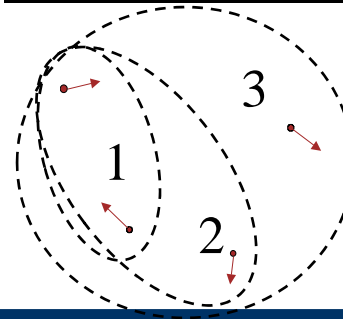


Coupled breadth-first fingerprint matching: expansion of k-plets is similar to tree searching.

Algorithm Features:

- True tree-based indexing
- Local connections between triplets (bins) are accounted for
- Matching test fingerprint against the tree is equivalent to matching against one template
- Fewer bins, but more structure and separability

Current implementation design:



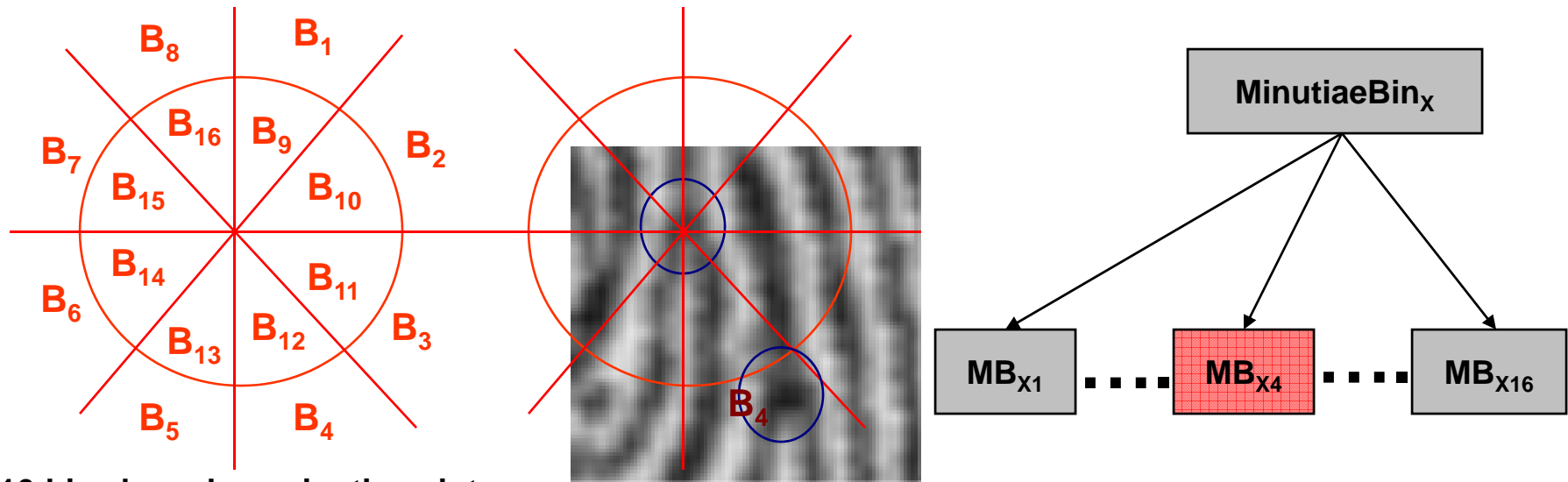
- K-plet is a single minutia
- The expansion of k-plets = search for nearest minutia



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Branch Selection

- Branching on each level is done based the relative features of the current minutiae and its nearest neighbor.
- Finite number of bins are used to handle continuous-valued features.



16-bins based on minutia point position relative to centre point.

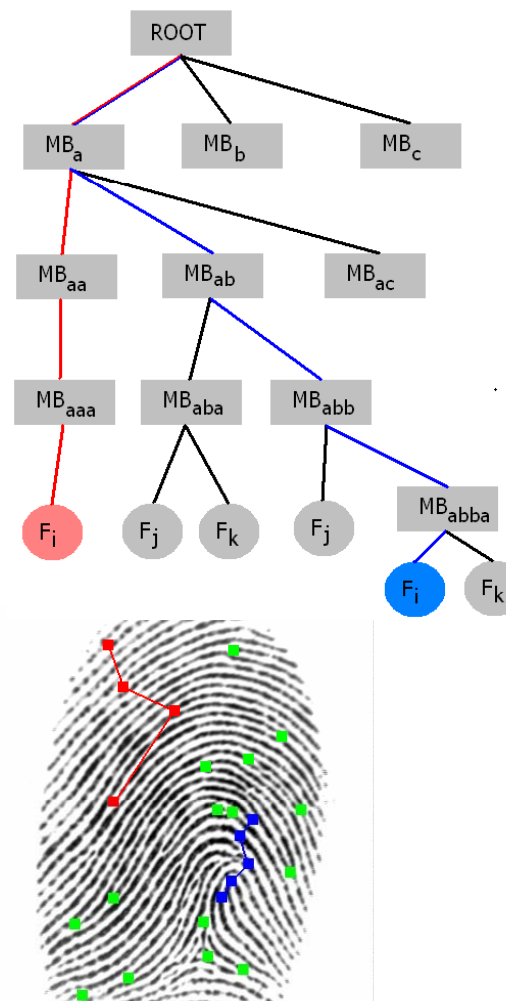


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Fingerprint Enrollment

- Fingerprint preprocessing and minutiae point extraction.
- One minutia point is selected as the root
- For each neighboring minutiae point, we traverse down the tree one level at a time and add the fingerprint at the appropriate leaf node.
- The process can be repeated for different points.

Thus we see that we do not need to rebuild the tree at a later stage while enrolling additional users into the system.



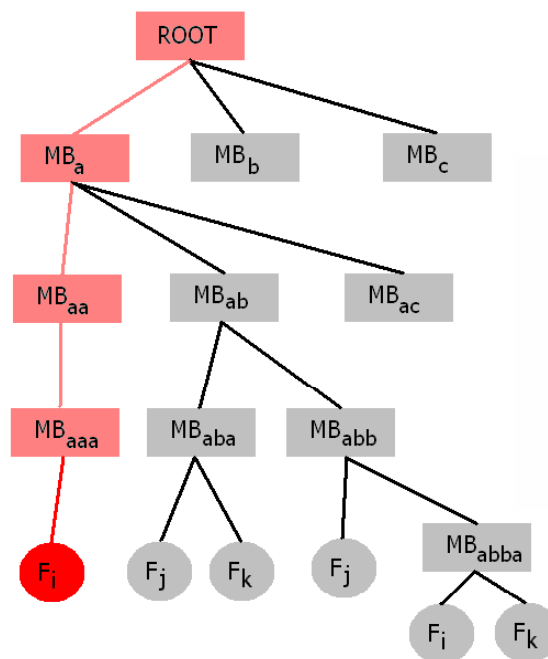


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Fingerprint Matching

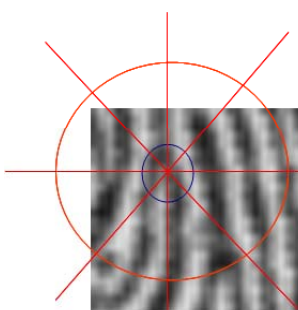
Single path matching:

- Fingerprint preprocessing and minutiae extraction.
- Select one point as root and find nearest neighbor. Calculate features of this point (neighbor) w.r.t. the current minutia.
- Based on the feature values, traverse down the tree, taking one minutia point at a time.
- Repeat by taking other minutiae as roots

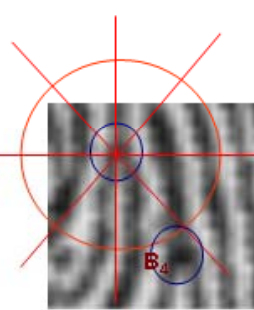


Multiple path matching:

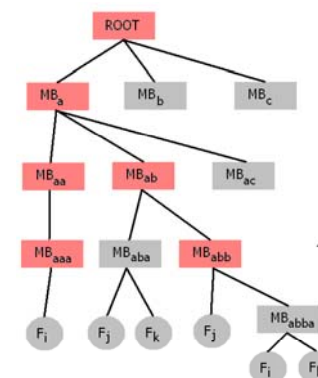
- If some minutia is close to the bin boundary, explore alternative matching paths



Searching Phase



Enrollment Phase





Single path search:

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FVC 2002 DB1	N = 5	N = 6	N = 7	N = 8
Correct	0.43	0.41	0.19	0.10
No Matches Found	0.08	0.55	0.81	0.90
Incorrect	0.49	0.04	0	0
Average Returned Matches	1.42	1.03	1.00	1.00

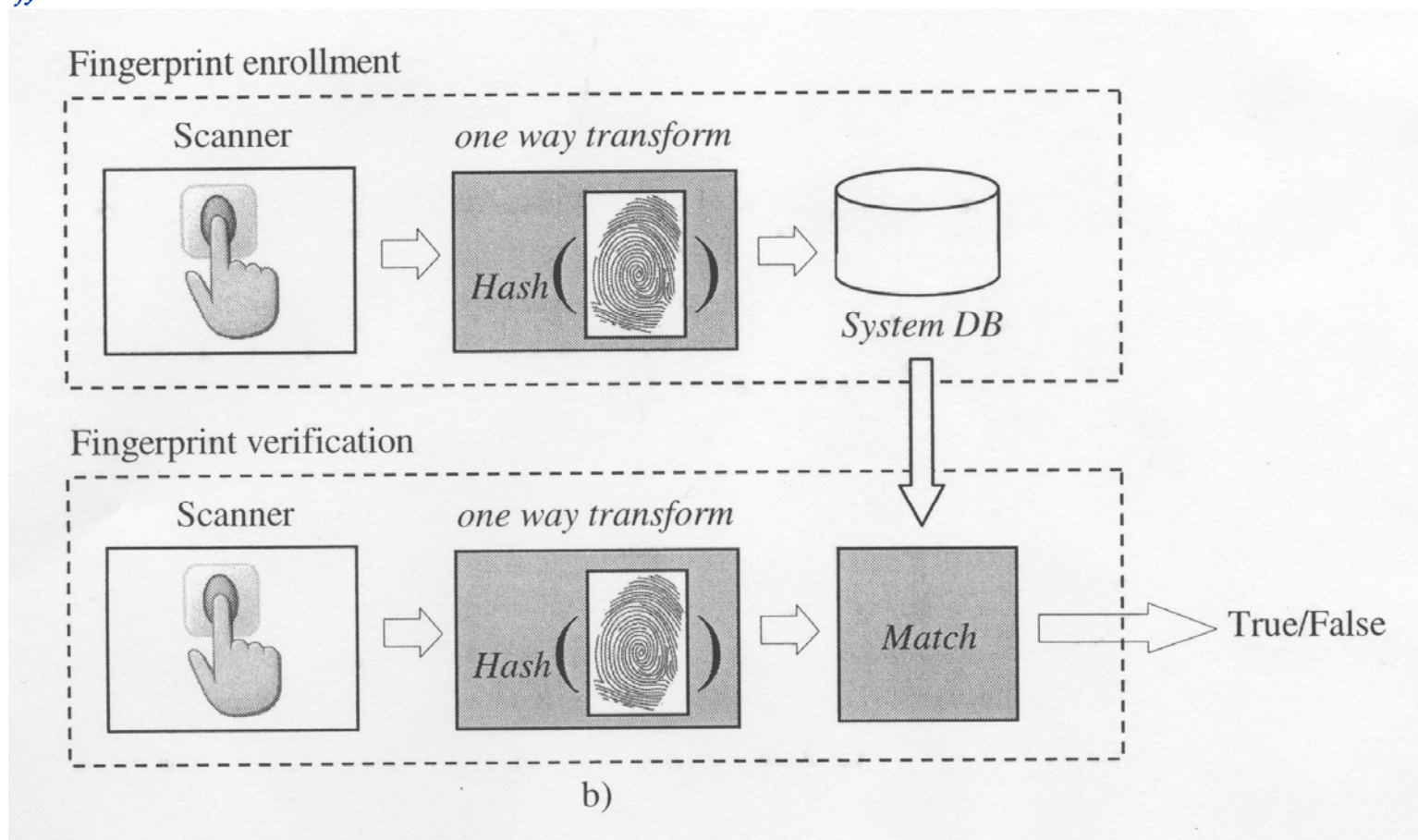
Multiple path search:

FVC 2002 DB1	N = 5	N = 6	N = 7	N = 8
Correct	0.32	0.58	0.44	0.30
No Matches Found	0.02	0.28	0.55	0.70
Incorrect	0.66	0.14	0.01	0
Average Returned Matches	1.29	1.08	1	1

Time:

FVC 2002 DB1	N = 5	N = 6	N = 7	N = 8
Single Path Search	0.112	0.032	0.028	0.028
Multiple Path Search	0.106	0.096	0.146	0.230

Cancelable Fingerprint Templates

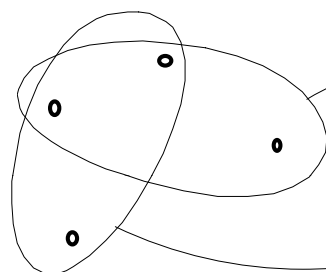


Local neighborhood minutia for hashes:

Fingerprint enrollment



Image



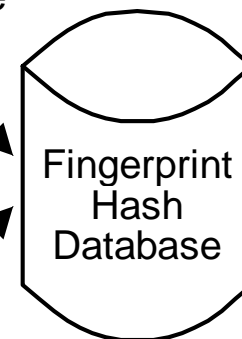
Minutiae

h_{11}, h_{12}

h_{21}, h_{22}

Hashes

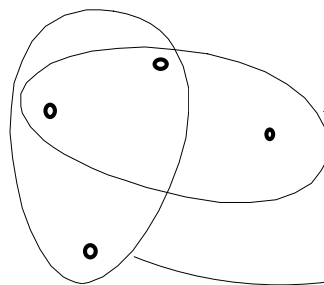
Store



Fingerprint verification



Image



Minutiae

h'_{11}, h'_{12}

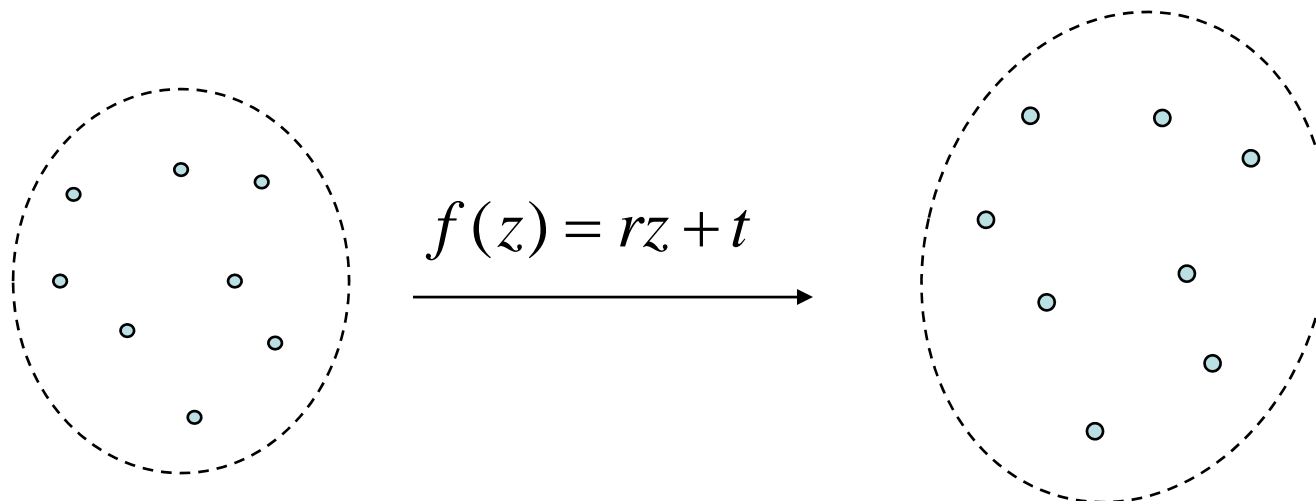
h'_{21}, h'_{22}

Hashes

Match

Assume rigid transformation between fingerprints:

If (c_1, c_2, \dots, c_n) is a set of minutia points of first fingerprint and $(c'_1, c'_2, \dots, c'_n)$ is a set of minutia points of second fingerprint (same finger), then we assume that there is a transformation $f(z) = rz + t$ such that $c'_i = f(c_i) = rc_i + t$ for any $i = 1, \dots, n$.





Hash Functions of Each Local Minutia Set:

Consider following functions of minutia positions:

$$h_1 = h_1(c_1, c_2, \dots, c_n) = c_1 + c_2 + \dots + c_n$$

$$h_2 = h_2(c_1, c_2, \dots, c_n) = c_1^2 + c_2^2 + \dots + c_n^2$$

⋮

$$h_m = h_m(c_1, c_2, \dots, c_n) = c_1^m + c_2^m + \dots + c_n^m$$

The values of these symmetric functions do not depend on the order of minutia points.



Hash Functions of Transformed (Test) Fingerprint:

$$\begin{aligned}h'_1 &= h_1(c'_1, c'_2, \dots, c'_n) = c'_1 + c'_2 + \dots + c'_n \\ &= (rc_1 + t) + (rc_2 + t) + \dots + (rc_n + t) \\ &= r(c_1 + c_2 + \dots + c_n) + nt = rh_1(c_1, c_2, \dots, c_n) + nt\end{aligned}$$

$$\begin{aligned}h'_2 &= h_2(c'_1, c'_2, \dots, c'_n) = c'^2_1 + c'^2_2 + \dots + c'^2_n \\ &= (rc_1 + t)^2 + (rc_2 + t)^2 + \dots + (rc_n + t)^2 \\ &= r^2(c_1^2 + c_2^2 + \dots + c_n^2) + 2rt(c_1 + c_2 + \dots + c_n) + nt^2 \\ &= r^2h_2(c_1, c_2, \dots, c_n) + 2rth_1(c_1, c_2, \dots, c_n) + nt^2\end{aligned}$$



Finding Transformation Parameters From Hash Values:

$$h'_1 = rh_1 + nt$$

$$h'_2 = r^2h_2 + 2rth_1 + nt^2$$

And r,t can be calculated given h_1, h_2, h'_1, h'_2

In practice:

- Consider also hashes of minutia directions

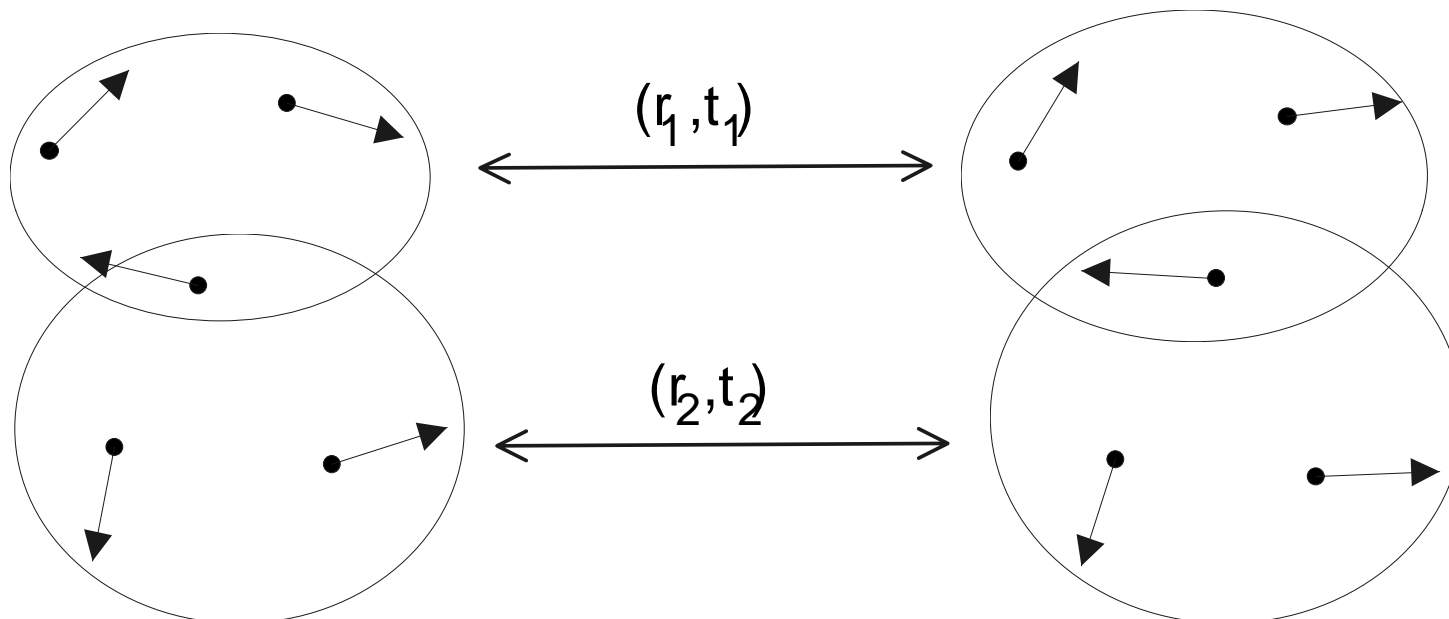
$$g_i(d_1, d_2, \dots, d_n) = d_1^i + d_2^i + \dots + d_n^i$$

- Search for transformation parameters minimizing distance functions

$$\begin{aligned} \text{dist}(h_i, h'_i, g_i, g'_i, r, t) = & \alpha_1 |h'_1 - rh_1 - nt| + \alpha_2 |h'_2 - r^2h_2 - 2rth_1 - nt^2| \\ & + \alpha_3 |g'_1 - rg_1 - nt| + \alpha_4 |g'_2 - r^2g_2 - 2rtg_1 - nt^2| \end{aligned}$$

Global Matching – Combine Local Matches

- Finding global transform parameters:

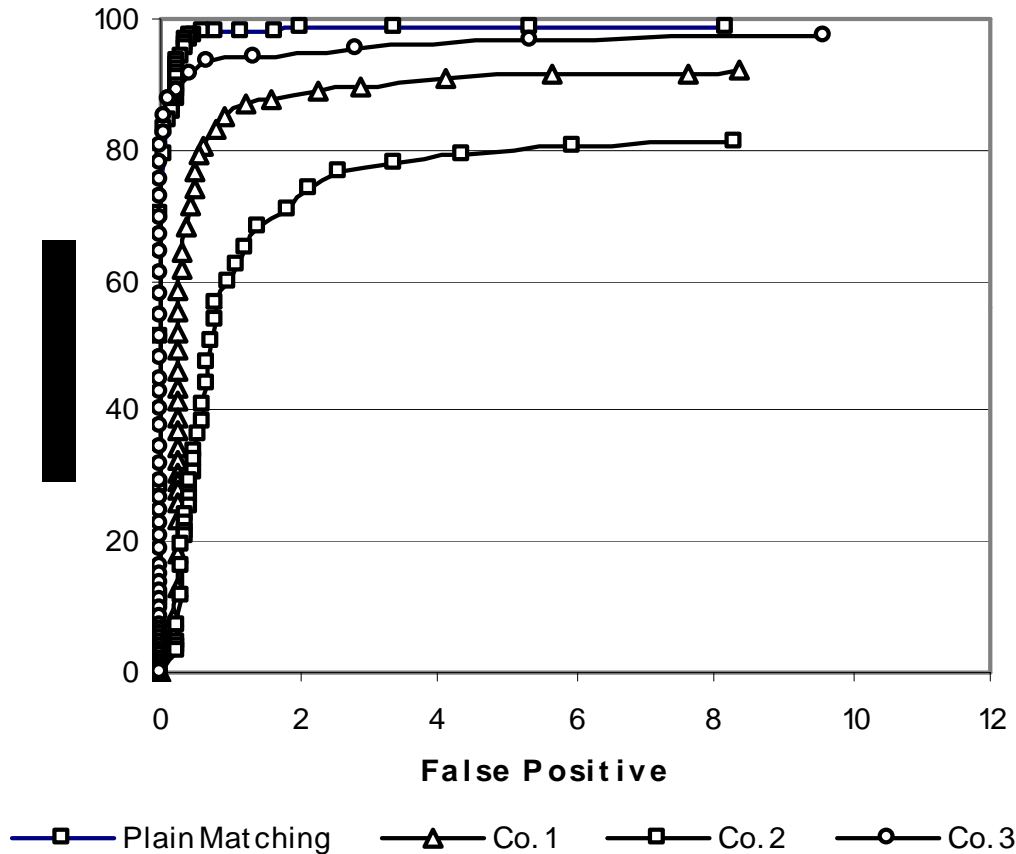


Find a cluster of (r_i, t_i) , $i = 1, \dots, n$



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Experimental Results



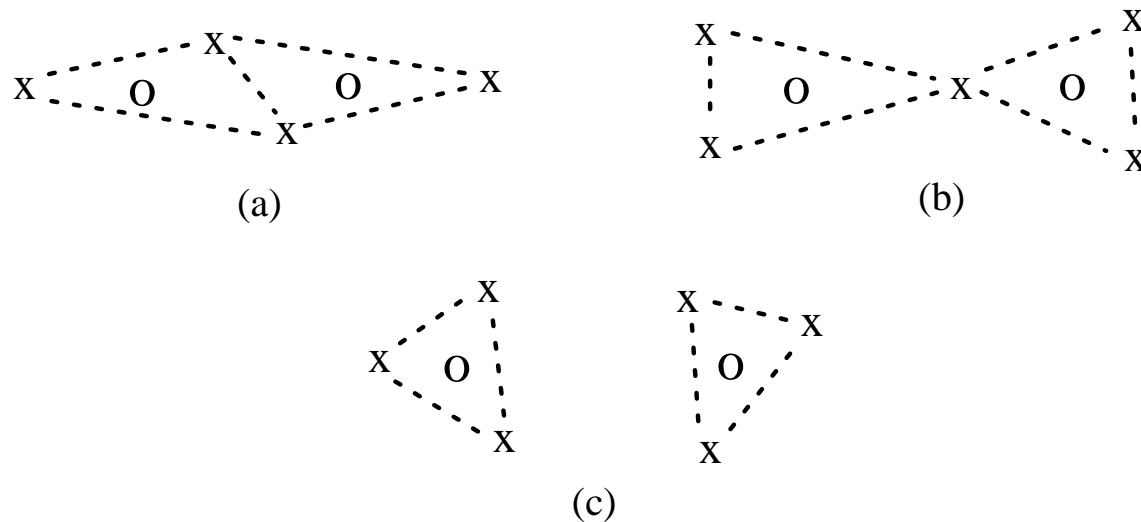
Co.3: 3 minutiae and 2 hashes
ERR = 3%

Original no-hash matching
ERR = 1.7%

Co.2: 3 minutiae and 1 hash
Co.1: 2 minutiae and 1 hash

tested on FVC2002 set,
with 2800 genuine tests
and 4950 impostor tests

- If the number of stored hash functions h_i is less than the number of minutia points, it is not possible to find the positions of minutia points c_j from local hash values.
- Using system of hash equations is difficult, since it is not known which minutia correspond to particular hash value.



Generating New Hashes

$s_i = s_i(c_1, c_2, \dots, c_n), i = 1, \dots, m$ - basis of symmetric polynomial functions of degree less or equal than m .

Then $s'_i = s_i(rc_1 + t, rc_2 + t, \dots, rc_n + t)$ are also symmetric, polynomial functions of degree less or equal than m .



For some predetermined $F : s'_i = F(r, t, s_1, \dots, s_m)$



r, t can be found from hash sets
 $\{s_1, \dots, s_m\}$ and $\{s'_1, \dots, s'_m\}$

Conclusion: *any basis in a set of symmetric polynomial functions can be used for hashing*

Example: $s_1(c_1, c_2, \dots, c_n) = a_{11}h_1(c_1, c_2, \dots, c_n)$
 $s_2(c_1, c_2, \dots, c_n) = a_{21}h_2(c_1, c_2, \dots, c_n) + a_{22}h_1^2(c_1, c_2, \dots, c_n) + a_{23}h_1(c_1, c_2, \dots, c_n)$